Vessel Segmentation of Coronary X-ray Angiograms

Irina Andra Tache
Department of Automatic Control and Systems Engineering
University Politehnica of Bucharest
Bucharest, Romania
irina.tache@acse.pub.ro, irina.andra@gmail.com

Abstract—The tagging of blood vessels from medical images is an essential step in the computer aided diagnosis of the vessels’ diseases. Different approaches, such as the Frangi vesselness filtering, the seeded region growing, and the adaptive thresholding are tested in order to obtain the vessels mask from the X-ray cardiac angiograms. The spurs are cleaned with morphological operations and the final results are tested with gold standard images.

Keywords— segmentation, seeded region growing, adaptive thresholding, angiography

I. INTRODUCTION

The advanced methods of image processing and data analysis are applied or adapted to medical field. The mathematical algorithms for segmentation are the first step in the image analysis and implicitly one of the most important tasks in computer aided diagnostics.

During the past decades there have been developed dozens of vessel segmentation methods each ones applied to different image acquisition types, from which the most important are the magnetic resonance angiography and X-ray angiography. Pattern recognition techniques [1], model-based approaches, tracking-based approaches, neural network-based approaches, morphological operations, wavelets [2], active contours [3] and non-linear filtering methods are some of techniques found in the scientific literature for solving this problem for the X-ray angiography. Survey papers dedicated to this topic can be found in [4-6].

The X-ray angiograms are affected by different kinds of noises with a Poison distribution. In order to compensate these noises, non-linear filters such as Frangi vesselness and Gabor filtering are implemented for vessel enhancement and compared in a previous paper [7]. The most important step in multi-scale vessel enhancement filtering is how to choose the appropriate range of spatial scales. The scale is related to the vessels dimensions, and it is discovered after multiple testing.

Also morphological operations are helpful when the objects needs a smoothly outline or for removing highlights smaller than the structure element.

In this paper three different segmentation algorithms for coronary X-ray angiograms are tested and compared with gold standard images obtained from two experts.

The first algorithm uses the Frangi vesselness filtering for vessel enhancement, global thresholding then morphological operations for removing the spurs.

The second algorithm uses an adaptive thresholding to obtain the vessel mask and then the morphological operations for removing the spurs.

The third algorithm applies the seeded region growing method on the maximum magnitude image from the Frangi vesselness filtering and then morphological operations for removing the spurs.

The algorithms are evaluated having as gold standard two vessel masks provided from two different medical experts. The comparison of the reliability of the three segmentation methods is made by using standard indices found in the scientific literature [8-9] from which the most important ones are the specificity and sensitivity.

The paper is organized as following: in the section 2 some explanations about the image acquisitions are made as long as the principal image processing methods used in the proposed algorithms, in the section 3 the results are presented and finally the conclusions are drawn in section 4.

II. MATERIALS AND METHODS

A. Data Acquisition

Coronary X-ray angiography is a medical imaging intervention which consists in the administration of a contrast agent into the local blood stream and the irradiation with X-rays for visualizing the inside of vessels lumen. It is performed during both diagnostic and interventional procedures of stent or bypass implants.

The data was taken from the Coronary Catheterism Laboratory in the Floreasca Emergency Hospital in Bucharest using standard clinical procedures. The image characteristics are provided into the Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Cardiac</th>
<th>Cerebral</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of images per series</td>
<td>70</td>
<td>30</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>512x512</td>
<td>1024x1024</td>
</tr>
<tr>
<td>Temporal resolution</td>
<td>15 images/second</td>
<td>3 images/s</td>
</tr>
<tr>
<td>No. of images stored for image</td>
<td>8</td>
<td>10</td>
</tr>
</tbody>
</table>

Because of the low pass characteristics of X-ray systems, the sharpness of the visualized coronary arteries is limited (images are blurred), which become especially visible when zooming in on interesting parts of the image.

For diagnosis purposes high quality visualization of the branches, stenosis and aneurysms is needed. Therefore, post
image enhancement which offers a better perception of the objects of interest facilitates the extraction of the necessary information from the image and could assist the cardiologists in appreciating the finer details of the coronary anatomy.

B. Seeded Region Growing

The region growing is one of the simplest and effective algorithms used in image segmentation.

It starts from a seed point which is the initialization of the object segmentation and the algorithm will search for similar pixels in the 3x3 neighborhood. The criteria of similarity for a pixel x was the minimization of the distance between the intensity of the pixel and the mean of the intensities of all pixels in its neighborhood.

The selection of the seed point could be made manually or automatically using some preprocessing of the image. Also by selecting multiple initial pixels the algorithm is called multi-seeded region growing. Generally, the object is divided in sub-regions and for each one a seed point is given.

C. Adaptive Thresholding

This method separates the foreground from the background with non-uniform illumination. In comparison with the global thresholding for which a fixed threshold is computed for the whole image, the adaptive thresholding computes a local threshold for a neighborhood with a predefined width.

Local adaptive thresholding selects an individual threshold for each pixel based on the range of intensity values in its local neighborhood. This is useful for images with a strong illumination gradient or whose global intensity histogram doesn't contain distinctive peaks.

The size of the neighborhood is not easily determined because it has to be large enough to cover sufficient foreground and background pixels, otherwise a poor threshold is chosen.

D. The Proposed Algorithms

In the followings three different segmentation algorithms are listed with their detailed steps for an easier reading.

The steps of the first algorithm are:

1. The generation of the maximum magnitude response of the Frangi vesselness filtering from the raw image.
2. Some morphological operations: dilatation, opening, erosion with a structural element with disk-shape
3. The global thresholding using the Otsu's method
4. Morphological operations for removing the spurs, filling the holes and removing small elements (opening operation)

The second algorithm steps are:

1. Adaptive thresholding with a specified local window,
2. Morphological operations for filling the holes, removing the spurs and small elements (opening operation)

The third algorithm steps are:

1. The generation of the maximum magnitude response of the Frangi vesselness filtering from the raw image.
2. The user selects a vessel pixel from the image
3. The application of Seeded Region Growing method
4. Morphological operations for filling the holes, removing the spurs and small elements (opening operation)

All these methods are developed taking into consideration the minimization of the computational time and the easiness of implementation.

III. RESULTS

The proposed algorithms from the section 2.D are implemented into Matlab® 2011b as well as the evaluation tools (the manual selection of the vessels contours by an expert, the mask generation and the computation of the evaluation indexes).

A. The Gold Standard Image

Two manual reference segmentations drawn by two experts represent an approximation of the ground truth.

Taking into consideration a test image, the mask images of the vessels selected by two different experts are presented into the Fig 1 a, b.

![Fig. 1 The golden standard masks selected by the first expert (a) and the second expert (b)](image_url)

As it can be observed from the above images, the second expert selected only the main vessels of the trunk therefore, the essential objects. In comparison, the first expert is more accurate and includes even the medium and small vessels into the golden standard mask.

B. The Results of the Proposed Algorithms

The algorithms proposed into the section 2.D are implemented and the resulted image masks are presented into the Fig. 2 to 4.

![Fig. 2 The mask resulted after the implementation of the first algorithm](image_url)
For the multi-scale Frangi vesselness filtering the scale range is from 1 to 5. The bigger the scale, the more noises where introduced in the maximum magnitude response.

For the image test from the Fig. 1 the global threshold that was used to convert an intensity image to a binary image was 0.4. The level is a normalized intensity value that lies in the range \([0, 1]\).

For the algorithm 2, the adaptive thresholding method was implemented using a local window with the size of 30.

For the algorithm 3 which uses the seeded region growing, a single manual pixel was selected on the right coronary artery.

After visual inspection of these three images, we can observe that the catheter is presented in all of them, because it has a tubular shape and it is included in the vessel trunk. Even if algorithms 1 and 3 have used the operation of spurs removal, there are still affected by unwanted pixels.

C. The Validation of the Proposed Algorithms

The evaluation of the segmentation algorithms are presented into the followings paragraphs having as references the two gold standard masks generated in the section 3.A.

For each resulted mask from the section 3.D a different 2×2 contingency table or confusion matrix is generated and the following evaluation indices are computed: sensitivity, specificity, positive predictive value and negative predictive value. All these results are computed for both gold standard masks.

The sensitivity is computed with the equation 1 and the specificity in the equation 2, where TP represents true positive pixels – the vessel pixels correctly tagged, TN represents true negative pixels – the background pixels correctly tagged, FN is false negative – the vessels pixels tagged as background pixels and FP is false negative – the background pixels tagged as vessels pixels:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (1)
\]
\[
\text{Specificity} = \frac{TN}{FP + TN} \quad (2)
\]

Finally, the sensitivity measures the proportion of vessels pixels that are correctly identified and the specificity measures the proportion of background pixels that are correctly identified.

The second group of complementary indexes is: positive predictive value (in equation 3) and negative predictive value (in equation 4):

\[
\text{Positive predictive value} = \frac{TP}{TP + FP} \quad (3)
\]
\[
\text{Negative predictive value} = \frac{TN}{FN + TN} \quad (4)
\]

The Dice similarity index is another important and frequently used measure in segmentation evaluation. It is directly proportional to the intersection of the two image masks and it is computed as in the equation 5:

\[
\text{Dice similarity value} = \frac{2|S \cap G|}{|S| + |G|} \quad (5)
\]

Where S is the segmented image mask and G is the ground truth mask.

The image spatial resolution is 512x512 therefore the total number of pixels is 262144.

Each image segmentation is assimilated with a classification into at least two classes: object and background.

The distribution of pixels between the two classes for each algorithm was compared with the gold standard images into the tables 2 – 4 (the table 2 corresponds to the algorithm 1, the table 3 to the algorithm 2 and the table 4 to the algorithm 3).

<table>
<thead>
<tr>
<th>Condition positive (vessels pixels)</th>
<th>Condition negative (background pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>True positive – TP</td>
<td>False positive – FP</td>
</tr>
<tr>
<td>Expert 1</td>
<td>Expert 2</td>
</tr>
<tr>
<td>Expert 1</td>
<td>Expert 2</td>
</tr>
<tr>
<td></td>
<td>Condition positive (vessels pixels)</td>
</tr>
<tr>
<td>------------------</td>
<td>-------------------------------------</td>
</tr>
<tr>
<td>True positive – TP</td>
<td>Expert 1 6528</td>
</tr>
<tr>
<td>False negative – FN</td>
<td>Expert 1 4651</td>
</tr>
</tbody>
</table>

**Sensitivity**

- Expert 1 0.5840
- Expert 2 0.6943
- Expert 1 0.9988
- Expert 2 0.9987

**Specificity**

- Expert 2 0.9526
- Expert 2 0.9888

**TABLE 3. THE CONFUSION MATRIX FOR THE SECOND ALGORITHM**

From the results showed in the tables 2-4 it can be concluded that the algorithms succeeded to have higher sensitivity rates for the second gold standard mask, with a maximum value of 86.73% for the algorithm 3. This means that all of the three algorithms tagged especially the principal vessels.

The image resulted from the algorithm 3 still has many unwanted pixels, but it succeeded to better approximate even the small vessels, due to its higher value of sensitivity (81.87%) computed for the first gold standard mask which is more accurate in showing all the vessel trunk.

Because of the high number of background pixels into the image, the specificity for all three methods is high – more than 98%.

Also, another important evaluation index is the Dice similarity measure. It is computed for all three algorithms and it is used for making the final comparison between the methods in the table 5.

**TABLE 5 – THE DICE SIMILARITY INDEXES COMPARISON**

<table>
<thead>
<tr>
<th>Dice index</th>
<th>Expert 1</th>
<th>Expert 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm 1</td>
<td>0.7797</td>
<td>0.8134</td>
</tr>
<tr>
<td>Algorithm 2</td>
<td>0.7254</td>
<td>0.8032</td>
</tr>
<tr>
<td>Algorithm 3</td>
<td>0.8268</td>
<td>0.7989</td>
</tr>
</tbody>
</table>

From the Dice indexes it can be easily observed that the algorithms 1 and 2 comply better with the second gold standard because they succeeded to identify only the main vessels (with values more than 80%) in opposition with the algorithm 3 which included the small vessels. With a Dice index of more than 82% the algorithm 3 complies with the first gold standard.

**IV. CONCLUSIONS**

Even if there are many methods developed for extracting the blood vessels, each ones are dependent by the image type, vessels type and by the standard medical procedures.

Three different segmentation algorithms for the coronary X-ray angiography are implemented and evaluated into this paper. Their main goal was to develop a good segmentation of the vessels with short computational time.

After the evaluation of the algorithm 3 which comprises the application of the single seeded region growing method on the maximum magnitude response image resulted after the Frangi vesselness filtering, it can be concluded that it better succeeded to detect the small vessels. For removing the spurs the opening morphological operation was used.

All three algorithms include the catheter tube into the vessel trunk. A further work could be to design the vessels model and to use it for removing all the tubular structures which do not comply with the model.
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